Entity-based Sentiment Classifier for Social Media Analysis

Master Thesis Seminar

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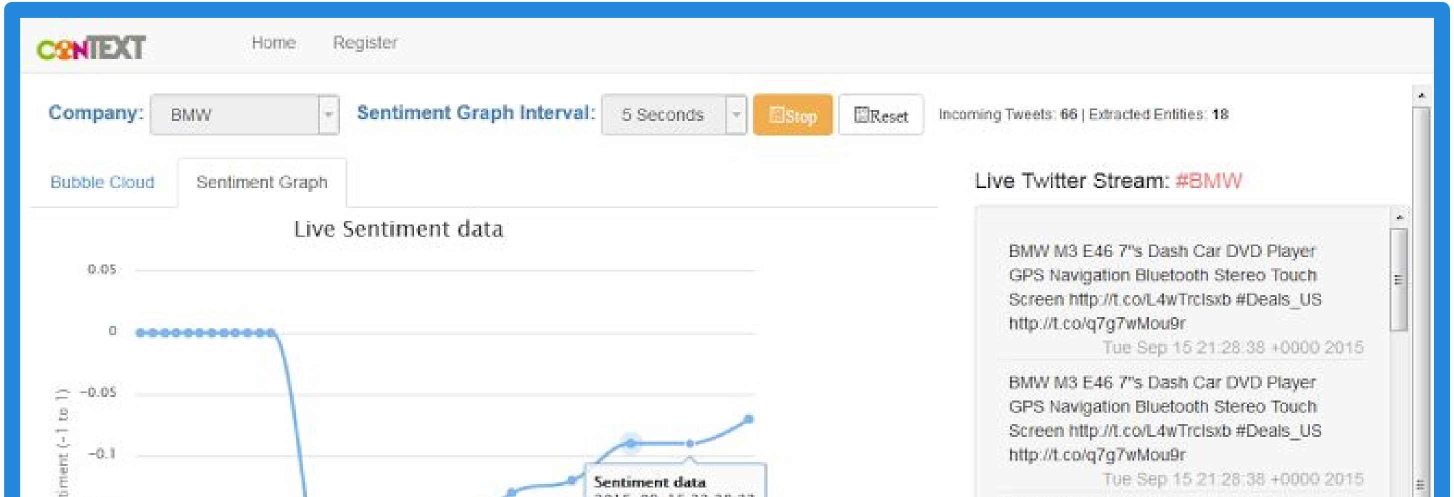
EIS
ENTERPRISE INFORMATION SYSTEMS

Motivation

- Social media networking services such as **Twitter** provide a massive amount of valuable data.
- Core business processes such as **market-sensing**, customer acquisition and customer relationship management (CRM).
- Cross domain applications: **Politics**, Sociology and others.

Motivation - SentiTrack

- **Linked Data-based Social Media Analysis for Stock Market Tracking**
    - **ReSA** (Real-time Sentiment Analysis) by Dr. Ali Khalili
    - Find correlation between **public sentiments** and intra-day **stock prices**

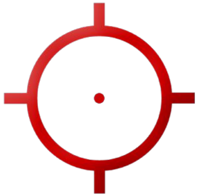


Problem definition

- **State-of-the-art approaches**
  - **Entities** are usually ignored
  - Only **document-level** analysis
  - Not designed for **tweets**
  - Presence of **multiple** entities
- **Real-Time Systems**
  - **Performance** issues

Objective

***"Classify* the sentiment of tweets according to the opinion expressed towards a *target entity*"**



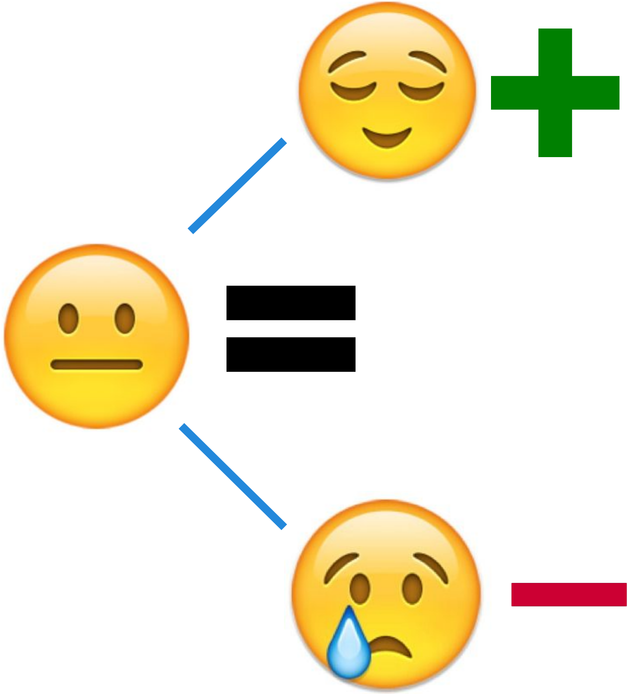
"my iPhone is <u>better than</u> your Nexus 4"

Entity *Entity*

Solution Proposed

- **Entity-based Sentiment Classifier**
  - **3-Class** Machine Learning approach
  - **Identify** and categorize entities
  - Entity **context** extraction
  - Entity-based **features**
- **Datasets for training**
  - Collection of **target-labeled** tweets

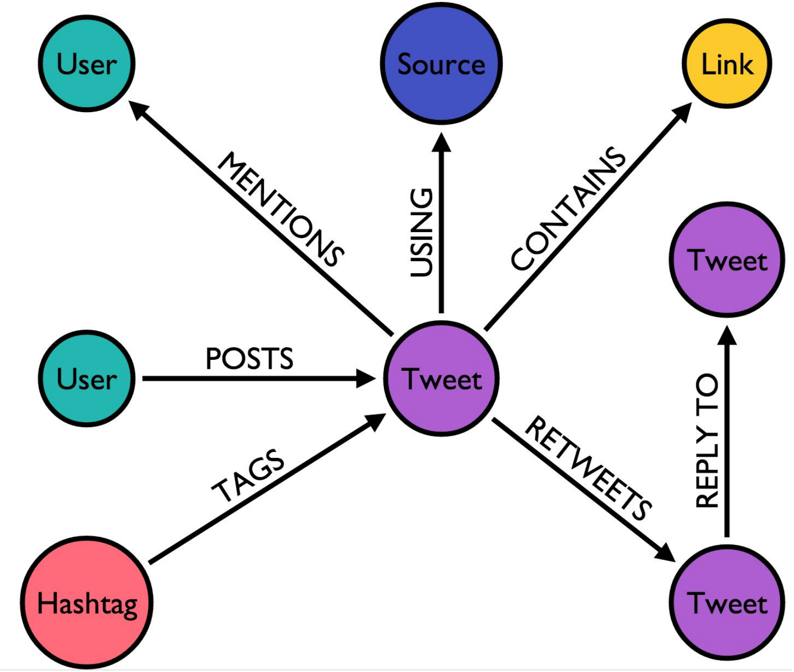
Background - Sentiment Analysis



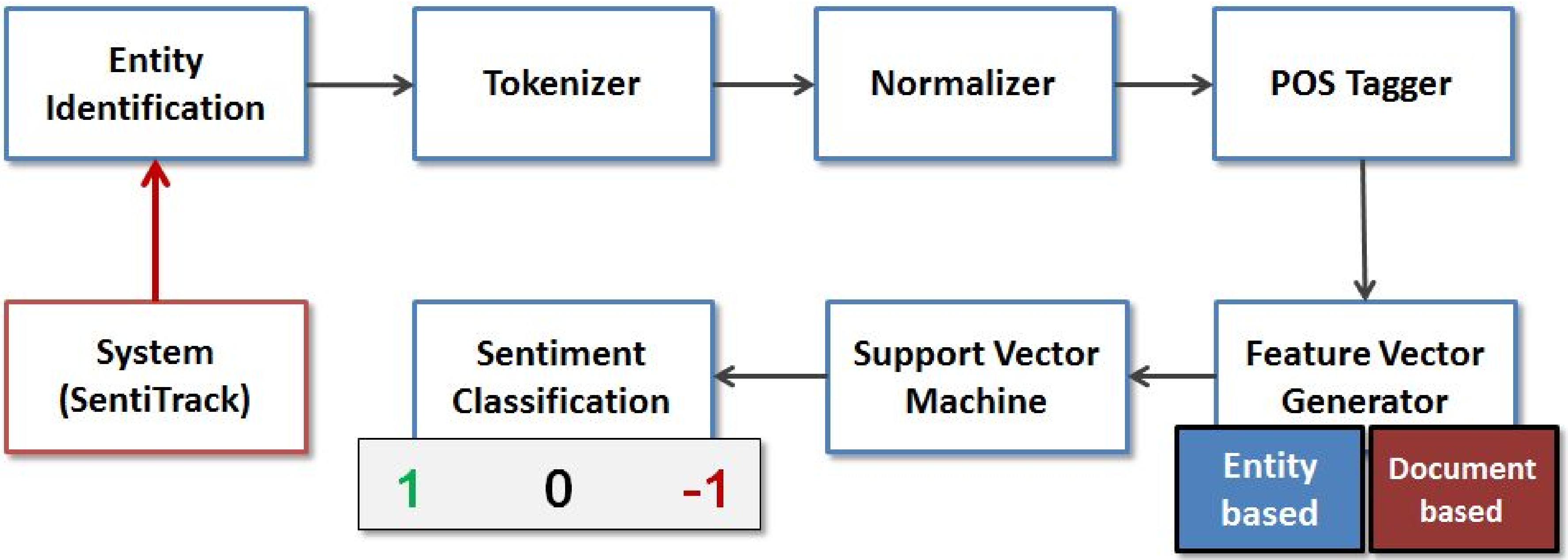
- **Extracting Opinions**
  - NLP / IR Task
  - Analysis **levels** (3)
- **Classifiers**
  - Supervised / Unsupervised
  - Classification **classes**
  - Polarity / Subjectivity

Background - Twitter

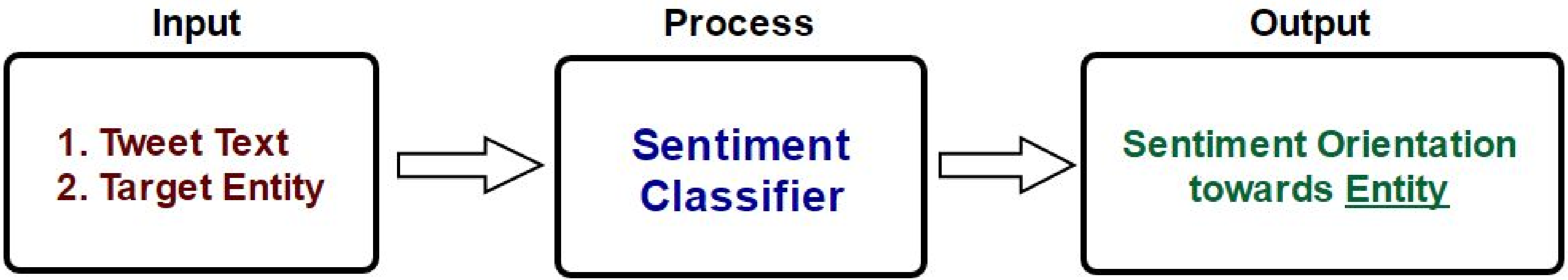
- **Features**
  - Short and concise
  - Slang / Abbr.
  - Unique **elements**
- **Twitter API**
  - **Real-Time** analysis
  - **Query** based search



Approach - Overview

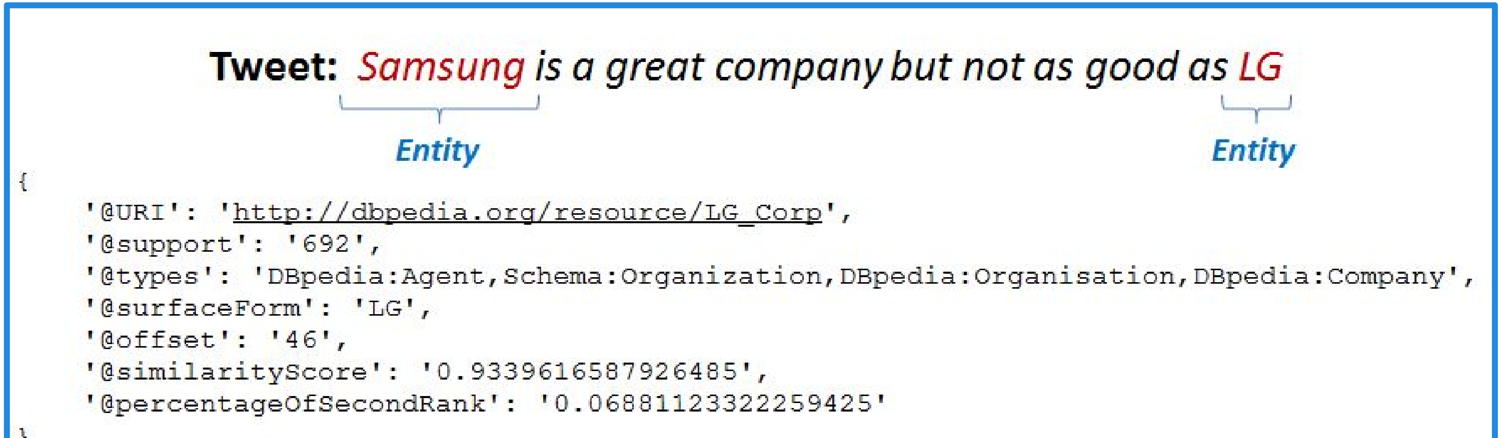


Approach - Workflow



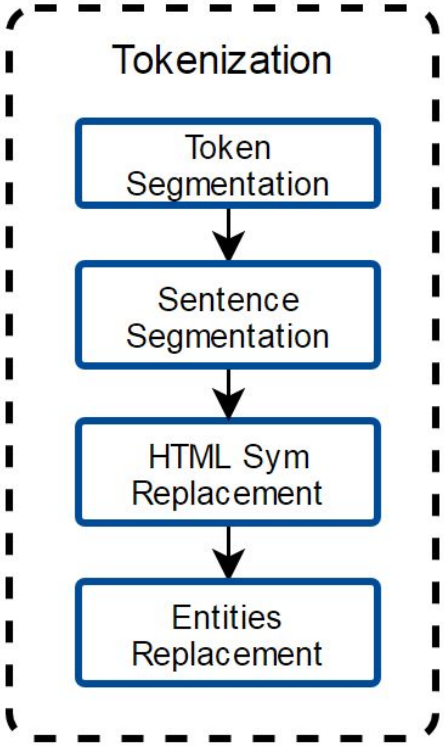
Approach - Entity Identification

- **DBpedia Spotlight**
  - Input **labeled** entities (Company / Person / Product) from SentiTrack
  - **Forward array** of entities (Target and Others) to Tokenizer module

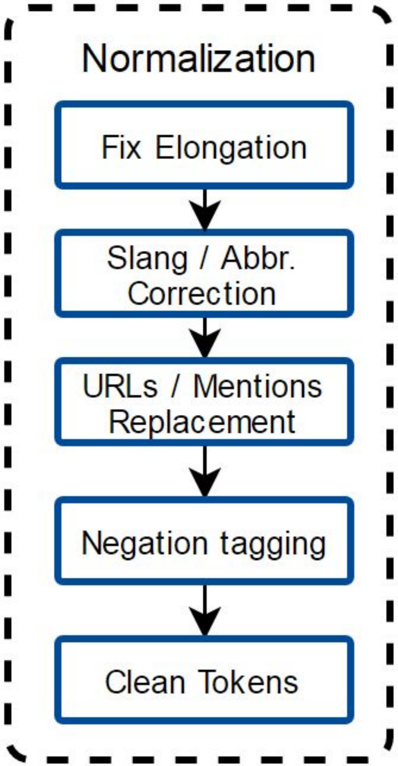


Approach - Tokenizer

- **Tokenization process**
  - **Splitting** of tweets into tokens using Regex
  - Identify sentence finalization tokens to for sentence separation (Regex)
  - Replace **HTML elements** with real values
  - Entities are replaced by **placeholders** to reduce sparsity of feature vectors.



Approach - Normalizer



- **Normalization process**
  - Fix tokens with more than two **repeated** letters
  - Replace slang and abbreviations with **correct form** (Urban Dictionary)
  - Replace URLs and @Mentions with **placeholders**
  - Tag tokens with "_NEG" that follow a **negated word** (not, never, none, etc...)
  - Remove numbers and symbols (Except Emojis)

Approach - Example Normalizer / Tokenizer

Target Entity	(1) Google
Other Entities	(1) Nexus
Tweet	Thanks google!! Just got my new Nexus <3
Result Tokens	(1) {Thanks, TargetEntity!!} (2) {Just, got, my, new, OtherEntity, <3}

Tokenized

Normalized

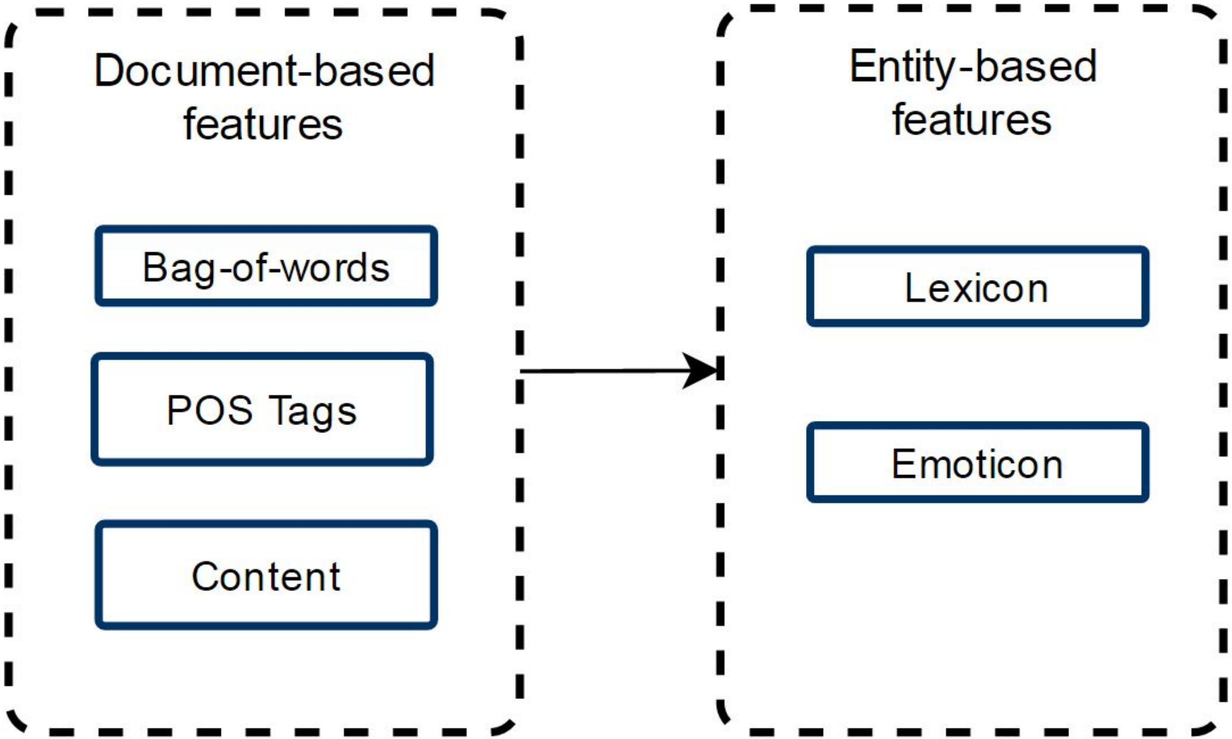
Tokens	**Normalization Result**
(1){not, their, best, !}	(1){not, their_NEG, best_NEG, !}
(2){ http://t.co, @Muse, #LiveMuse}	(2){ someURL, someUser, #LiveMuse}

Approach - POS Tagger

- **Part-of-speech tags on tokens**
  - Twitter ARK POS Tagger (Carnegie Mellon Uni) java-based
  - Most relevant tags are: *Nouns* / *Adjectives* / *Verbs* / *Adverbs*

Normalized Tokens	POS Tagging
(1){not, their_NEG, best_NEG}	{R/not, O/their_NEG, A/best_NEG}
(2){ someURL, someUser, #Live}	{ someURL, someUser, #/#Live}

Approach - Feature Vector Generator



FVG / Document - Binary Bag-of-words

- **Boolean term frequency**
  - Vector space reduced by removal of Stopwords
  - Values can only be 1 or 0, present or not

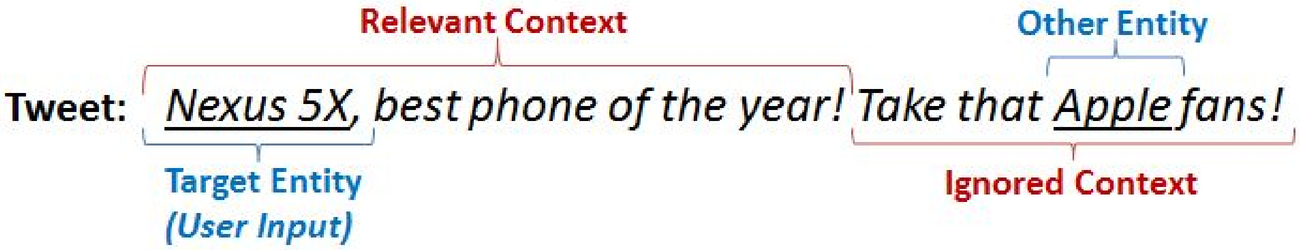
Tweets	Binary Bag-of-words
happy birthday friend! :)	{1,1,1,1,0,0,0}
always be happy ;)	{1,0,0,0,1,1,1}

FVG / Document - POS Tags / Content

- **POS Tags Features**
  - No. of Nouns / Adjectives / Verbs / Adverbs
- **Content Features**
  - No. of all-caps, hashtags, elongated words, negation context, punctuation.

FVG / Entity - Context Extraction

- **Sentence separation**
  - Ignore **non-target sentences** (Outside Neighborhood) for Entity features
- **“But” clause and conditions**
  - Rules for condition expression (“except that, but, better than”)



FVG / Entity - Lexicon

Lexicons	Score Range	Words
MaxDiff	Real-values	1,500
AFINN	-5 to 5	2,477
BingLiu	Pos / Neg	6,785
SentiWordNet	-1 to 1	147,292
MPQA	Pos / Neg	6,886
NRC Hashtag	Real-values	54,129
Sentiment140	Real-values	62,468

- **Lexical Resources**
  - Different **score ranges**
  - All 3 types of lexicons
- **Calculations**
  - **No.** sentiment tokens
  - **Total** score
  - **Max** score
  - **Last** token score

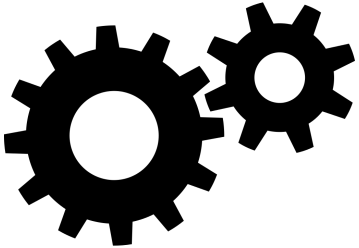
FVG / Entity - Emoticons / Example

- **Emoticon Features**
  - Resource Pos / Neg emojis (SentiStrength)
  - No. of Pos / No. of Neg

Target-entity context tokens	Feature Vectors
{my, TargetEntity, is, awesome,	(BingLiu){2, 2, 1, 1}
best, day, ever, :D }	(Emoji){1,0}

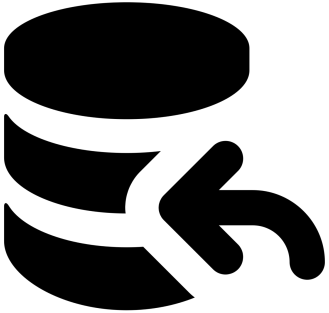
Approach - Support Vector Machine / SentiTrack

- **Node-SVM (LibSVM)**
  - Linear kernel with **default** parameters
  - No class weighting (balanced training data)
  - Active sparse format to **ignore** 0 in vector space
- **SentiTrack - common technologies**
  - **Node-js** implementations
  - Modular integration with **.npmjs** (Node Package Manager)

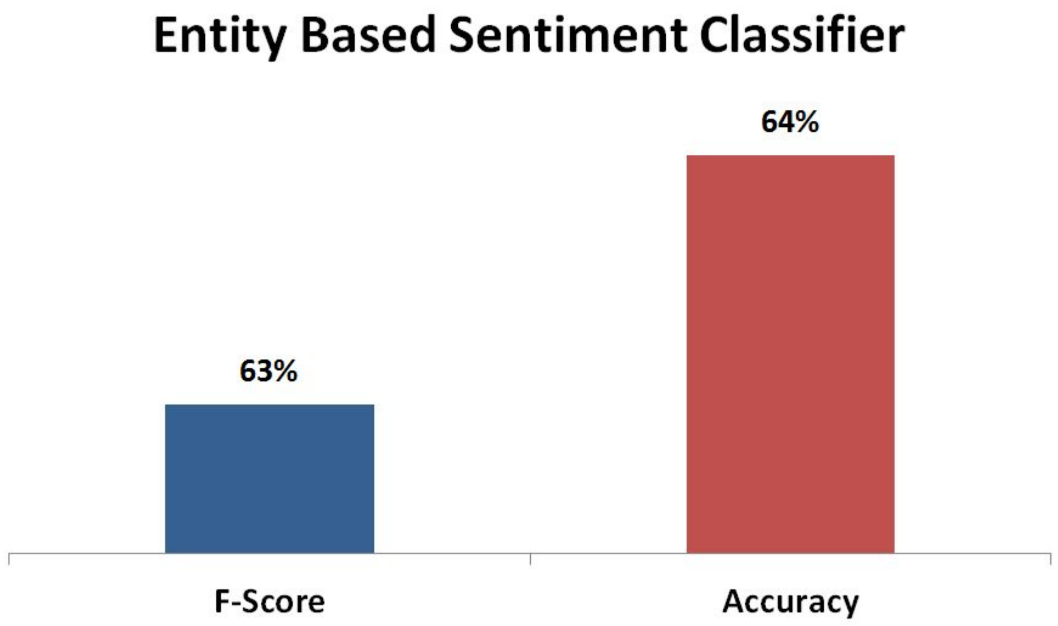


Evaluation Results - Datasets

- **Collection**
  - Semeval 2015 (**Semantic Evaluation**) - Task 10 - Training data
  - Semeval 2016 - Task 4 - Training data
  - Twitter **Sanders** Analytics Corpus
  - **STS** - Gold (Saif M. Mohammad)
- **Data Summary**
  - **4900** entity-based annotated tweets (balanced classes)
  - **70%** - 30% SVM Training / Eval ratio

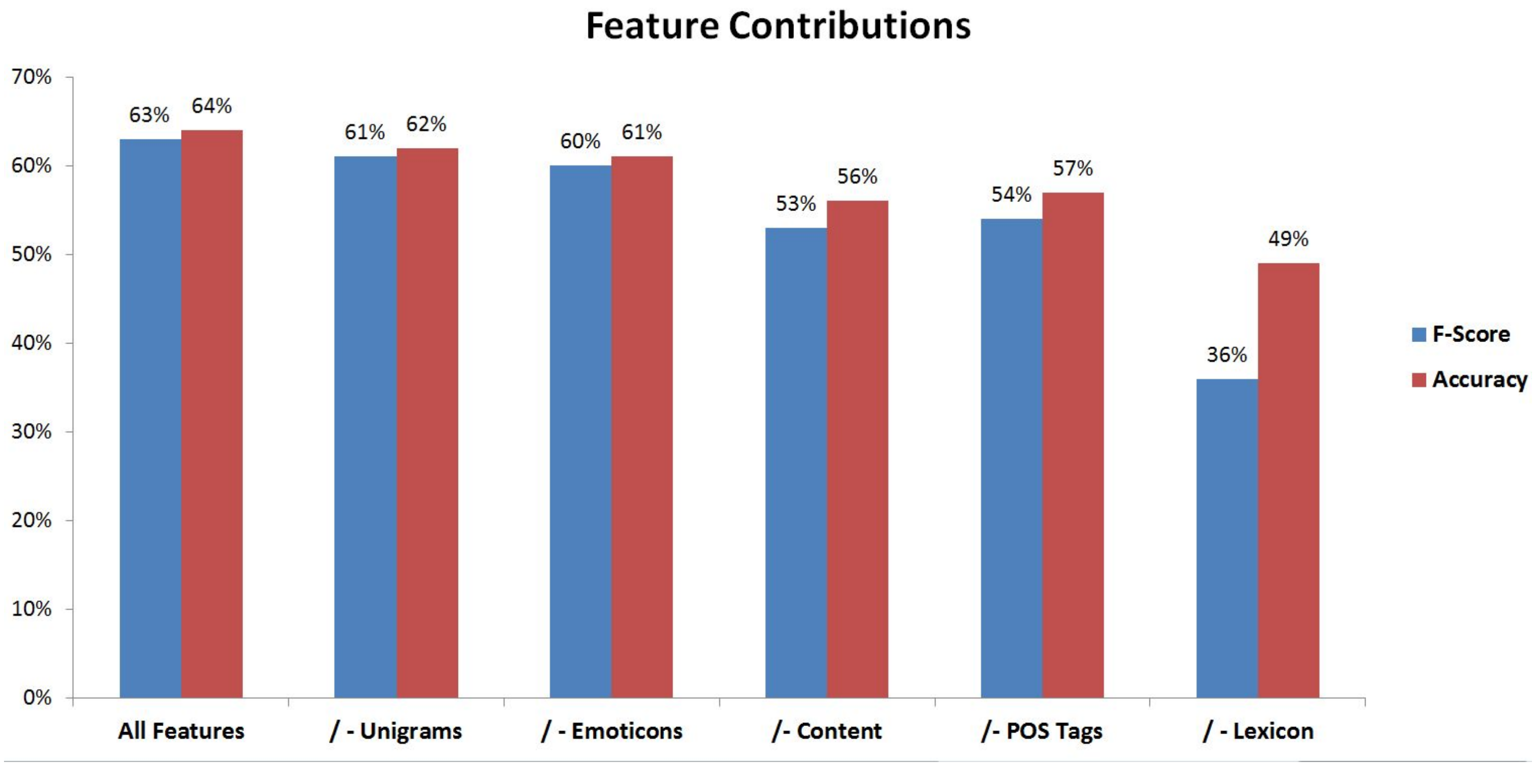


Evaluation Results - Quality

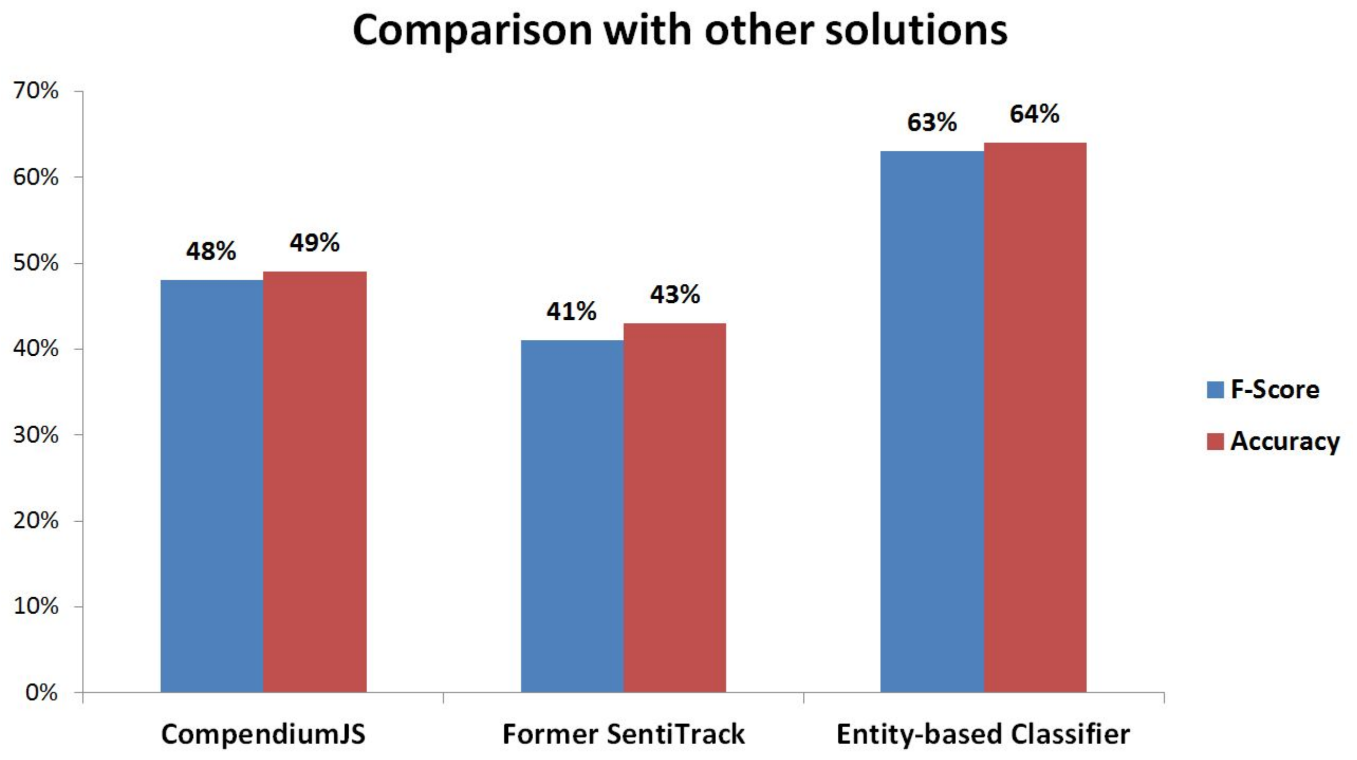


- **Evaluation Metrics**
  - F-Score / Accuracy
  - 4-fold **cross validation**
  - **Features** quality test
  - **70%** - 30% training / eval ratio

Evaluation Results - Quality



Evaluation Results - Comparison



Evaluation Results - Performance

- **Evaluation environment**
  - Intel Core i5-2320 CPU @ 3.00GHz
  - 8 GB RAM
  - 64 bits Windows 7
- **Results for 1000 tweets processed**
  - Former SentiTrack Classifier: **323 ms**
  - CompendiumJS: **2357 ms**
  - Entity-based Classifier: **3447 ms**

Conclusions

- This thesis presented the **research, solution and evaluation** of an entity-based sentiment classifier for social media analysis
- Implemented sentiment classifier was **fully integrated** to SentiTrack and ReSA. Which proves its compatibility with real-time systems
- Proposed approach achieved **satisfactory results** with 20% accuracy **improvement** over former SentiTrack classifier

Future Work

- Expand the sentiment classifier with a **dependency parser** module capable of performing real time analysis
- Improve the quality of the classifier by including higher level **n-grams** and a better **Named Entity Recognition** module
- Develop a **graphical user interface** that allows users to classify tweets
- Enhance Support Vector Machine module by the inclusion of **distant supervision** methods

SentiTrack...

Thank You

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